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## COVER PAGE

### A Review and Simulation of Business Angel Investment Returns

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#### Author Bios

Geoff Gregson is the JR Shaw Research Chair in the JR Shaw School of Business at the Northern Alberta Institute of Technology (NAIT) in Edmonton, Canada and is a Visiting Researcher with the Institute for the Study of Science, Technology & Innovation (ISSTI) at the University of Edinburgh. He was previously Deputy Director of the Centre for Entrepreneurship Research at the University of Edinburgh Business School. His areas of academic research include private equity financing; technology commercialisation; strategic leadership and corporation innovation; and exploitation of intellectual property (IP). As an entrepreneur, he started up and managed two ventures and has experience as Chairman and non-Executive Director with UK-based and international businesses.

Adam J. Bock is Associate Professor of Business at Edgewood College in Madison, Wisconsin. Adam has taught Entrepreneurship and Management courses at the University of Edinburgh, Imperial College London, and the University of Wisconsin-Madison. He has given dozens of executive seminars on technology venturing, innovation commercialization, and private financing. Most recently, Adam spent five years on faculty at the Business School at the University of Edinburgh. Adam is the co-Founder of two medical device companies spun-out of university research programs, and the Founding CEO of a third. He has served as a non-executive director and has provided advisory consulting for numerous early stage technology firms and start-ups.

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# **TITLE PAGE**

## **A Review and Simulation of Business Angel Investment Returns**

## **Abstract**

Business angels are widely recognized as a significant source of entrepreneurial finance, particularly for early stage businesses. However, rigorous investigation on angel investment performance has been limited. This paper examines investment returns of business angels in addressing the question of whether angel investing generates attractive returns. We review the few published studies which report on more than 100 investment exits to establish baseline returns expectations and clarify returns measurement limitations. We then use data from one of the largest studies of angel returns to populate a monte carlo simulation of returns profiles based on portfolio size and other key characteristics. The simulation explores the link between portfolio size and the probability of the desired level of returns. The study reveals that angel deal returns are highly skewed; smaller portfolios have higher average returns but dramatically lower median returns. In contrast with prior studies, our study shows that portfolios with more than 50 investments are required to significantly minimize risk of poor returns and that similar scale is required to maximize returns potential, as smaller portfolios have a lower average internal rate of return (IRR). We show that reinvestment rate is a critical element in measuring angel returns and we demonstrate the limitations of IRR as a returns metric through the simulation. We compare findings against returns from venture capital (VC) investing and discuss theoretical, practitioner and policy implications.

Key words: business angels, investment returns, portfolio size, policy implications

## **1 Introduction**

The market for early-stage investments has grown dramatically in the past decade with the rise of the business angel investor, who typically makes small investments in early-stage ventures (Kim and Wagman, 2016). Formal angel investments in the United States are estimated to exceed \$20 billion annually, roughly half the total of institutional venture capital (VC), with recognition that angels fund more businesses than VCs because average deal size is smaller (NVCA 2016; CVR 2015). Many scholars believe that the informal angel market is significantly under-measured (Kerr et al, 2014; Wiltbank, 2005).

Despite the growth of angel investing and its importance in funding early stage ventures, rigorous investigation on angel returns has been limited, compared to studies on VC performance (e.g. Capizzi, 2015; Wiltbank et al, 2009; Shane, 2008, 2009; Mason and Harrison, 2002; 2008), especially from a portfolio perspective. This is partly due to the inherent challenge of collecting data on angel investments (Mason and Harrison, 2002; 2008) and divergent opinions on how to measure returns (Capizzi, 2015).

Evaluating angel investment performance is important for a number of different stakeholder groups. For scholars of entrepreneurial finance, angel investing appears disadvantaged compared to professional VC investing. Angel activities face high coordination costs, limited access to information, reduced negotiating power, and limited follow-on investing potential (e.g. Wiltbank

et al, 2015, 2009; Van Osnabrugge, 2000). Angels appear to invest in the higher risk, early-stage market, where VC funds are much less active (Mason and Stark, 2004). Studies of long-term VC returns report highly skewed results, in which the top quartile of investments drive total portfolio results (Ball et al 2011; PWC-NVCA, 2015). Assuming angel investing results are similar, it is unclear whether angel investments generate rewards commensurate with the risks.

For angel investors, better understanding of exits and portfolio investing could improve investment decision-making and potentially attract more high net-worth individuals to become angels. One question that remains elusive in the literature is under what conditions do angels make money from their investment exits? (Mason et al, forthcoming).

For policy makers, entrepreneurial activity is hindered by the so-called ‘equity funding gap’ (Cumming, 2005). High-growth ventures (referred to as ‘gazelles’) often require more capital than founders can source from family and friends, but less than VC round minimums (Sohl, 2003). Regional economic activity may suffer when angel activity is unnecessarily suppressed or ineffective, especially if angels cannot reinvest exit-based returns into new ventures. (Mason and Harrison, 2006). This is particularly the case following the collapse of the so-called funding escalator following the 2007-08 global financial crisis (Harrison 2013; North et al 2013; Harrison and Baldock 2015). One question arising from the literature is whether or not policy makers should subsidize angel investing to support regional economic and job growth if angels are not generating appropriate risk-adjusted returns (Mason and Brown, 2013; Gregson et al, 2013; Shane, 2009).

In this study, we review ten published studies which report on more than 100 investment exits and utilize monte carlo simulation to more rigorously explore angel investing returns. By varying portfolio size and investment timing, we can more carefully assess the risk-reward profile of angel investment activity. We use data from the largest of the ten studies, the Angel Investor Performance Project (AIPP) dataset, which collected information from 539 angel investors, to populate our monte carlo simulation. Each “profile” comprises 9000 portfolios and more than 2 million randomized investments selected from the dataset. By comparing profiles across characteristics of interest, we can systematically address unresolved questions about angel investing returns.

Our findings align with prior research showing that increasing portfolio size reduces risk and provides more stable returns. However, in contrast with prior studies, our study shows that portfolios with more than 50 investments are required to significantly minimize risk of poor returns and that similar scale is required to maximize returns potential, as smaller portfolios have a lower average internal rate of return (IRR). This is significantly larger than previously suggested (12-20 investments) and exceeds the capabilities of the vast majority of most angel investors and angel investing groups. We report returns using both IRR and MIRR (modified IRR). We discuss the benefits and drawbacks of these returns metrics and show that key policy and practice implications can be derived from the simulation and analysis.

The paper proceeds as follows. Section 2 provides a background to the study and relevant literature. Section 3 then reviews and compares the results of prior studies on angel investment returns. The dataset and simulation method is described in Section 4. Section 5 discusses

simulation results, followed by Section 6, which discusses the implications of findings for theory, practice, and policy. Section 7 provides conclusions, study limitations and suggestions for further research.

## **2 Background to Study**

A business angel ('angel') is a high net-worth individual investing personal funds in privately held companies, usually start-ups (Mason and Harrison, 1996). Angel investments often address the "equity funding gap," investing more than entrepreneurs can raise from their own resources but less than the minimum investment threshold of VC funds (Sohl, 2003; Cumming, 2005).. The gap is generally accepted to range from approximately \$100,000 to \$5 million, depending on region (Sohl, 2003), and represents the absence of small amounts of risk capital from institutional sources for early-stage companies.

Angels that invest personal funds have the flexibility to choose deals for nonfinancial as well as financial reasons and compared to venture capitalists (VCs), have no pressure to maximize investment returns or exit within a particular time horizon (Mason and Harrison, 2008). A smaller percentage of angels only invest in high-potential ventures; some angel groups focus entirely on high-risk/high-reward ventures. These groups are typically more sophisticated and professional regarding their investment practices (Gregson et al, 2013; Mason et al, 2006).

Angels have attracted increasing attention from policy makers as important actors in regional economic development, as they are shown to invest in more new businesses than VC (Mason et al, 2013; Gregson et al, 2013). However, there has been little systematic evaluation of the costs to government of supporting risk capital or evidence-based analysis of preferred mechanisms for government intervention in angel investing (Da Rin et al, 2011). By comparison, numerous studies on venture capital inform policy. For example, Puri and Zarutskie (2011), using US Census data, find that only 0.11% of new companies created over a 25 year sample period from 1981-2005 are funded by VC, yet these companies account for 4% to 5.5% of employment. They show that VC-backed companies grow faster at every stage of the investment cycle, i.e., both before and after the receipt of VC.

### **2.1 Portfolio Investing**

Angels also engage in the pooling of funds or investment syndication, in addition to investing as individuals. Pooling or syndication attempts to diversify investments and reduce overall risk exposure (Brander et al, 2002), without giving up individual control over investment decisions. In the US, angel syndicates are a growing source of funding for new and emerging businesses seeking investments under \$1million (Sohl, 2012). In the UK, angel syndication has been shown to yield larger investment deals, more follow-on investments, but fewer new investments and fewer exits (Gregson et al, 2013). Most angel returns data has been generated from angel groups, which engage in more formalized data gathering and reporting than individual angels; a topic that we will discuss further in the paper.

A key unresolved question in the literature relates to investment portfolio diversification. There is no definitive benchmark for how many investments are required to improve the risk/reward profile. Some prior studies suggest a minimum of 12 to 20 investments (Teten 2013; Wiltbank, 2012). In contrast with such predictions, this paper draws on portfolio theory to hypothesize that much larger portfolios are required to provide protection against returns variability and to significantly decrease low IRR portfolio outcomes.

## **2.2 Measuring Angel Investment Returns**

A common ‘metric’ to measure and compare investment returns since the early days of private equity has been internal rate of return (IRR) (Gompers and Lerner, 2001; Freear et al, 1995). Both VC and angel communities have adopted IRR as the primary method for measuring the effectiveness of investments and for comparison purposes (Wiltbank & Boeker, 2007; Aernoudt, 2005; Wiltbank, 2005; Mason & Harrison, 2002). IRR provides annualized rates of return and a value weighted measurement that takes into consideration the timing of cash contributions and distributions (Johnstone 2008).

The fundamental problem with IRR as a metric is the underlying assumption that positive cash flows are effectively reinvested at the same rate of return (Phalippou 2008). IRR calculations are highly sensitive to the timing of cash outflows and a large pay-out after a longer time period can work out to a lower IRR than smaller, but quicker, pay-outs that result in less cash returned overall to investors. Similarly, a second investment round just prior to the sale of the company, which generates a return almost immediately, can have a much higher IRR than an earlier investment, even if the earlier investment was at a much lower valuation and had a higher exit multiple. This illustrates the time element of the IRR calculation, where investments that tie up cash longer are punished (Chemmanur and Chen, 2014). Da Rin et al (2011) suggest that IRR provides an incentive to exit investments soon, even at the cost of forcing an outcome whose rate of return is lower.

In the case of angel investing, the use of IRR implicitly requires that cash inflows will be redeployed to more angel investments or an alternate asset class with a comparable risk-reward profile. Given that (1) angel investing is understood to have high variation in returns and (2) that the market for angel investing is very imperfect, with limited deal flow in most geographic areas, this assumption appears *prima facie* flawed.

To overcome IRR distortions, a modified IRR (MIRR) can be adopted, which is a variation of net present value (NPV) that is typically expressed as a rate of return (Da Rin et al, 2011). MIRR employs a discount rate derived from the fund’s cash flows and measures the growth in net worth due to the investment, so that there is a number at the beginning and one at the end of the investment (Phalippou, 2008). This addresses the issue of nonconventional cash flows, as the IRR calculation assumes that cash flows are reinvested each year at a constant rate. However, MIRR is not as widely used in comparative angel or VC returns studies as IRR. MIRR presents a different measurement problem in the specific context of portfolio-based angel investing due to the extended time frame of the portfolio (likely greater than 15 years). The reinvestment rate required for MIRR

analysis may dominate other returns effects, as will be seen in the simulation results and discussed later in the paper.

### **2.3 Additional Measurement Challenges**

Computing financial returns requires good data and a solid methodology that is widely shared by researchers (Da Rin et al, 2011) and both these requirements are challenged in angel returns research. Angels do not track IRR in a consistent manner, and many do not track return rates at all (Wiltbank, 2005). In order to standardize IRR calculations, data should include the date of investment, amount of investment, date of liquidity event or revaluation of investment, and value of the return. Even then, IRR as an investment returns metric has its own challenges, as described above. Concerns over uneven disclosure of returns and data quality are also identified with VC studies (Harris et al, 2014; Da Rin et al, 2011; Gompers et al, 2005).

The confidential nature of angel investing and differences in investment criteria amongst angels contribute to the difficulty in gathering and comparing angel returns data (Shane, 2009). Angels may intentionally keep a low profile and angel data that is self-reported may induce under-reporting of poorly performing investments. Public reporting therefore tends to focus on larger, syndicated deals, which can bias available data samples.

Methods to gather and compare angel returns data using either a cross-sectional or time series approach can also be highly problematic (Mason and Harrison, 2002). Survey response rates have generally been low, suggesting self-selection and non-response biases that might skew results (Kollmann and Kuckertz, 2009). Some scholars caution that studies of angel returns are subject to systematic, unreported and for the most part unacknowledged upward bias (Cumming and Walz 2010; Cochrane, 2005).

### **2.4 Comparing Angel and VC Returns**

Comparisons between angel and VC returns also requires caution, in acknowledging differences in investment practices. While angels make their own investment decisions, VCs follows a Limited partnership model, whereby investors (i.e. Limited Partners: LPs) provide fund managers (i.e. General Partners: GPs) with funding, but have no say in investment decisions. GPs are under pressure to source deals in the early years of a fund and achieve returns within a finite time period (typically 10-12 years), requiring a high volume of potential deal sourcing (Gray et al, 2015; Gregson, 2014). VC is described as a 'hits-driven' business, where a few significant returns can offset losses from the majority of investments (Ball et al, 2011).

Gompers and Lerner (2000) suggest that there is a limited number of favourable (i.e. high-return) VC investments that has to be matched with a fluctuating capital supply; giving way to the so-called 'money chasing deals' phenomenon. Comparisons between VC and angel returns should also account for the management fees charged by VCs, which are calculated on committed capital (typically 2.0-2.5%) but charged on called capital; the total amount of issued capital for which shareholders are required to pay (Mulcahy et al, 2012).



One question is the extent to which ex-ante differences between angels and VCs affect exit returns. Kerr et al (2014) observe that angels engage in efficient selection and screening just as traditional VCs do, while Cosh et al (2009) find that angels invest in ventures that exhibit similar characteristics as those in which VCs invest. Chemmanur and Chen (2014), postulate that if researchers can control for measure of value-adding activities of VCs and angels, then there should be no difference in an angel's or VC's portfolio exit rates. Schwienbacher (2009) argues that angels and VCs can both play value-adding roles, but that the key difference is that VCs have sufficient capital to refinance a company, whereas angels do not.

Different 'demand side' dynamics between angels and VCs may also influence returns. For example, it is suggested that angel financing is chosen by entrepreneurs because VC financing is simply unavailable in the early stages of the firm (Hellmann and Thiele, 2014). Studies confirm that VCs have shifted away from early-stage investing towards larger and later stage deals and tend not to invest in deals that seek less than three or four million dollars (OECD, 2011; Sohl, 2012). The pecking-order theory (e.g., Myers and Majluf, 1984) suggests that entrepreneurs seek financing in an order that minimizes ownership dilution, with debt financing preferred, but typically unavailable for early-stage ventures, and angel funding preferred to VC.

### 3 Prior Studies of Angel Returns

In this section, we review the limited number of angel studies to determine what they collectively reveal about angel returns. Table 1 summarises ten major studies which each report on more than 100 investment exits and which offer a higher level of statistical relevance than studies using much smaller samples. It can be seen that US and UK studies dominate the sample, which is not surprising, given that most large angel groups and syndicates are located in these two countries.

For our discussion, we identify corrected IRRs reported in the literature subsequent to release of the the original AIPP dataset (2007), which attempt to improve upon original IRR calculations. The differences between reported IRRs in original and corrected publications are not substantial (under two percentage points difference) in the context of this paper.

**Table 1: Summary of Investment Returns in Angel Studies (n>100 investments)**

Year of Study	Author(s)	Total Investments	Exited Investments	IRR
2013 US	DeGennaro & Dwyer: "Expected Returns... by Angel Investors in Groups"	588	419	69.9%
2010 US	Roach: "Keiretsu Forum"	120	Unknown	15-33%
2009 UK	Wiltbank: "Siding with the Angels"	1,080	406	24.6%
2009 US	Band of Angels	200+	Unknown	18.0%
2009 US	DeGennaro & Dwyer: "Expected Returns to Angel Investors"	603	434	33.0%

<b>2008-present US</b>	Sohl: "The Angel Investor Market in the US (Annual Report)"	Unknown	Unknown	20-30%
<b>2007-2012 Italy</b>	Capizzi, : "The returns of business angel investments"	553	143	17.6%
<b>2007 US</b>	Villalobos & Payne: "Startup Pre-Money Valuation"	117	117	24.3%
<b>2007 US</b>	Wiltbank & Boeker: "Returns to Angel Investors in Groups" ( <u>AIPP</u> )	3,097	1,137	31.4%
<b>2002 UK</b>	Mason & Harrison: "Is it worth it? The Rates of Return from Informal VC"	372	128	37.4%

What do previous studies reveal about angel returns? Two of the studies offer a range of IRRs rather than a calculated IRR. Sohl's annual study of US angel investment activity (University of New Hampshire Centre for Venture Research), finds that IRRs range from 20% to 30%, but this research does not provide details of return calculations such as holding period for investments, the sample size, or the unit of analysis for the investment.

The 2010 Roach study is of particular interest, as the study reported an investment failure rate of only 20%; lower than the rate of start-up failure in the U.S. The low failure rate and moderate but consistent returns (IRR range of 15-33%) suggest potential benefits to a diversified, portfolio approach to group-based angel investing. The Keiretsu Forum invests in a broader range of sectors, including non-technology opportunities such as real estate and incorporates investments across geographically dispersed chapters.

The DeGennaro and Dwyer study (2009) utilized a subset of the AIPP dataset reported in other studies, but the study restricted data to facilitate cash-based IRR calculations. This appears to have biased the data subset to higher returns investments; resulting in an average IRR of 69.9%.

Setting aside the DeGennaro and Dwyer, Sohl and Roach studies, the remaining seven studies in Table 1 show a range of returns between 17.6 and 37.4 percent, with an average IRR of 26.6%. The largest study, the 2007 Angel Investor Performance Project (AIPP), collected information from 539 angel investors who were members of 86 angel investor groups and who had experienced 1,137 exits from their investments. Over half the exits (52%) lost money (less than 1x return) while 7% of exits returned over 10x the original investment.

Original IRR calculations for the AIPP data yielded an IRR of 27%. However, Wiltbank and Boeker (2007) calculated average return by weighting each investment the same, regardless of time to exit (an issue identified by DeGenarro & Dwyer, 2009). Revised calculations by Right Side Capital Management (RSCM, 2010) used the average return multiple (2.6x) and the average holding period (3.5 years), which yields an IRR of 31.4%; suggesting that the original approach underestimates IRR. Further analysis of the AIPP data finds that the top 5% of investments accounted for 57% of all return payouts.

The 2009 Wiltbank study, based on a survey of 158 UK-based angels, found a similar skewing of returns as the 2007 AIPP study: 56% of exits failed to return capital and 9% generated more than 10x the capital invested. In this study, the original IRR was calculated at 22%. Revised calculations by RSCM (2010), using the same logic applied to the original AIPP data, used the average return multiple (2.2x) and the average holding period (3.6 years), which yields an average IRR of 24.6%; again, suggesting that the original study calculation underestimates IRR.

Mason and Harrison's 2002 study found that the distribution of returns was highly skewed, with 34% of exits at a total loss, 13% at a partial loss or break-even, and 23% showing an IRR of at least 50%. Only 10% generated IRRs in excess of 100%. Further analysis of Mason and Harrison's data (RSCM, 2010) attempted to determine IRR by making assumptions on each of five original performance-related data categories; yielding an average IRR of 37.4%.

Despite the variation in underlying datasets and reported returns, certain conclusions may be drawn from prior studies. First, angel investing appears to generate a relatively high IRR, at least comparable with, or possibly exceeding, published returns from venture capital. Second, the data on group-based investing, which is somewhat analogous to portfolio investing, suggests the potential for higher returns. Third, broadly speaking, larger datasets appear to generate higher IRR estimates.

### **3.1 Comparing Angel Returns with Venture Capital Returns**

The angel returns reported from prior studies are similar to VC returns in one respect, in that only a small percentage of investments generate the majority of liquidity. One difference is the wider variation in reported VC returns compared to angel returns. Bygrave and Timmons (1992) examined VC funds and found an average IRR based on net asset values of 13.5% for the years 1974-1989. By comparison, Chen et al (2002) examined 148 VC funds using Thompson Venture Economics (TVE) data set that had been liquidated before 1999 and found an annual average return of 45% (with a standard deviation of 115%). Analysis of data from the Thomson Financial US Private Equity Performance Index found that returns to *early stage* VC investments over a twenty-year period (1986-2006) were 20.5% (Cumming and Johan, 2010). Total VC returns for this same period were 16.5%.

The high variability in reported VC returns is attributed to a number of factors that include superior market timing abilities of fund managers during the harvest phase of the fund (Diller and Kaserer, 2009) and exogenous factors, such as the economic climate for initial public offerings (IPOs), which may drive exit valuations (Ball et al, 2011). Lerner et al (2007) suggest that VC fund performance is a good proxy for investor learning capacities. Other studies suggest that subsequent investments by an investor or group benefit from a learning and experiential effect (e.g. Harrison et al 2015; Wiltbank et al, 2009).

Mason and Harrison's 2002 study found that, compared to VCs, angels have fewer investments that lose money, a higher proportion of poor or moderately performing investments and a similar proportion of high-performance investments. They suggest that angels are more concerned with avoiding bad investments than 'hitting a home run' because of their limited ability to diversify.

Given the high failure rate of early stage ventures, it is surprising that angels have fewer investments that lose money than VCs, e.g. Headd (2003) suggests that the failure rate of new business is estimated to range from 24% to 34% after two years, approximately 50% after four years, and approximately 60% after six years. Wiltbank and Boeker (2007) suggest that angel investors may positively influence their investment returns by increasing due diligence time, avoiding portfolios in unfamiliar industries, and actively participating with their portfolio companies at least a couple of times per month. One criticism of these findings, which are based on the AIPP data, is that it is not clear whether higher returns are a direct result of these angel activities (DeGennaro and Dwyer, 2014).

Goldfarb et al. (2009) find that angel and VC deals have similar success rates when the amounts involved are smaller, but that angel-backed companies are more likely to become ‘living dead,’ with pure VC deals having a higher success rate when they involve larger sums. They conclude that entrepreneurs looking for more patient and less control-oriented investors seek angel financing whereas entrepreneurs looking for more managerial value-adding choose VCs.

Wiltbank et al (2015) suggests that angel investment in the U.S. generates greater returns on capital than VC investment. The study is based on 3,160 private firms acquired by US-quoted corporations between 1996 and 2006. The authors also differentiate between two types of firms; high capital-consumption firms, or ‘burners’, and low capital consumption firms, or ‘earners’, as shown in Table 2. Angel investment is predominantly with earners and VC investment with burners. Earners are more likely to fund growth with money from sales revenue and therefore require much less investment. Although they take much longer to reach an exit for the investors, the returns are significantly higher than for burners. Burners use large amounts of equity capital to fund growth but this significantly reduces their rate of return.

**Table 2: Comparing ‘Burner’ and ‘Earner’ Investment Returns**

	‘Burners’	‘Earners’
	high capital consumption	low capital consumption
paid in capital	\$25 million	\$95k
average growth rate	366%	151%
total cash out	\$58.1 million	\$23.5 million
years held	7.0	13.4
return on capital	12.6%	50.7%

In summarizing their findings, Wiltbank et al (2015) identify a strong ‘diminishing’ effect of paid-in capital on valuations; in other words, additional capital beyond a certain point did not significantly influence total valuation of firms at time of acquisition. Their findings suggest the importance of ‘patient capital,’ commonly associated with angel investors (i.e. earners) and of company building activities over a longer time period and outwith the ‘high growth’ norms of PE investing, that may positively influence investment returns.

## 4 Method: Simulating Portfolio-based Angel Returns

One important unresolved question from prior studies and the literature regards investment portfolio diversification. There is no definitive benchmark for how many investments improve the risk/reward profile, although previous studies and industry experts suggest a minimum of 12 to 20 investments (e.g. Teten 2013; Wiltbank, 2012).

To inform a deeper understanding of portfolio-based angel investing, we employ monte carlo simulation on one of the largest angel investment datasets to generate millions of hypothetical angel investment portfolios of varying sizes and characteristics. Monte carlo simulation is a proven method for exploring population dynamics and probabilistic outcomes when data is difficult to obtain (Mooney 1997). The analysis is inherently limited by how well the dataset represents the full population of angel investments, but provides important insight beyond prior studies that only report IRR for the dataset as a whole.

We frame our simulation of angel returns within portfolio theory, which suggests that the risk of poor returns is reduced when multiple investments are made to ‘spread’ the risk and reap the benefits of diversification of different investment opportunities (Elton and Gruber, 1995). The theory suggests two elements of risk in an equity investment; the first being market risk, which is systematic and cannot be eliminated. The second risk is firm specific, which is non-systematic and can be reduced by holding a diversified portfolio. Within a well-balanced portfolio of investments, the theory suggests the existence of a minimum level of co-variance between the different investments (Markowitz, 1959).

It is important to note that angel investing does not meet the stringent requirements for efficient markets. Investments are highly illiquid, difficult or impossible to objectively value, limited in number and access, and extremely idiosyncratic. The angel investing data demonstrates high returns variability across individual investments. Our application of “portfolio” theory is therefore limited to diversification to reduce risk via increasing the investment pool. We do not suggest that angel investing may be placed on the efficient frontier in a CAPM analysis. Nor do we explicitly address how angel investing deviates from CAPM with reference to other investment classes or types.

Our goal is narrowly focused on assessing the potential to reduce returns variability by increasing the size of the investment portfolio. Given the high levels of variability reported for individual angel investment returns, we hypothesize that much larger portfolio size ( $N > 25$ ) is required to provide significant protection against returns variability and low IRR portfolio outcomes.

### 4.1 Dataset

To test this hypothesis, we use data from the largest of the angel returns studies, the Angel Investor Performance Project (AIPP) dataset, to populate a monte carlo simulation of returns profiles based on portfolio size. For ease and simplicity, we used a publicly available version of the AIPP dataset published via Right Side Capital Management.

Original AIPP data were collected online through a questionnaire that asked for information on the investors' experience, the ventures in which they had invested, and details about their investment in and exit from those ventures. The data contains survey responses from 86 angel groups totaling 539 investors who had made 3097 investments, with 1137 exits identified from those investments: 8% of exits occurred prior to 2000; 30% of exits were from 2000 to 2003; and the remaining exits were since 2004; 90% of the initial investments occurred after 1994, and 65% were initiated after 1999.

A number of limitations should be acknowledged with the AIPP dataset. All respondents are members of angel groups; therefore, the dataset does not capture individual accredited angel investors and cannot be considered representative of angels in general. The average response rate from the angel groups (n=86) was 31% and the average response rate of members of those groups (N=539) was only 13%, suggesting that survey respondents may not be representative of the angel groups.

This raises the possibility of selection bias, also suggested by DeGennaro and Dwyer (2009), whereby respondents are those reporting good investment outcomes, with those with poor outcomes not responding. Wiltbank and Boeker (2007) acknowledge that generalization of findings should focus exclusively on angel investors who operate in groups. Selection bias is also suggested in the high percentage of AIPP investments that resulted in an IPO, which may inflate the reported performance of the angel groups which participated in the AIPP.

The publicly available version of the dataset had already been cleaned as follows:

- Some records showed investments with no start date or investment amount. These records were removed.
- Some records showed investments with a follow-on investment occurring prior to the original investment. These records were removed.

To implement monte carlo simulation, additional preparation of the dataset was required:

- Some records show a follow-on investment with no start year. A start year was calculated halfway between the latest investment and the exit year.
- Some records show a "mid-cash return" in which a net inflow was recorded without a date. A date for these was calculated as halfway between initial investment and exit year.
- Most records show an exit cash amount (failed investments show a "zero"). Seven records showed investments with zero cash in the "total return" field but no numerical amount in the exit cash field. Given the total return was zero, we entered zero for the exit cash for these records.

Two additional notes should be made about the dataset:

- One record shows a \$10,000 investment and a \$2.4M return in the same year. As reported in Wiltbank & Boeker (2007), the IRR of the dataset is approximately 31%. This single investment represents nearly one-third of that total return. Without this investment, the IRR of the dataset falls to 22%. While this is not necessarily a problem in the dataset, it is worth noting for the simulation. When this investment is selected into a portfolio, especially a small portfolio, simulation necessarily reports extraordinarily high returns.

- Of the 452 records in the dataset, 448 show investments that either pay out within 13 years or do not pay out at all. Four investments show a positive payout after 13 years. One pays out after 17 years, two after 25 years, and one after 35 years. The collective IRR of these long-hold investments is 11%. Excluding them from the dataset does not significantly change the measured return of the dataset. Including them significantly impacts MIRR calculations, however, as we will discuss.

## 4.2 Simulation Method

The monte carlo simulation process is briefly explained here. The simulation varies portfolio size, which ranges from 5 to 450 investments. Small portfolios generate effectively random return rates because of the high variability in returns of individual investments; we determined that there was no obvious value in generating portfolios of less than 5 investments. As the dataset includes approximately 450 investments, portfolios with more than 450 investments would not be expected to generate significantly different results.

For a given portfolio size (e.g. 50 investments), the simulation uses Excel's (pseudo) random number generator (McCullough & Heiser 2008) to select investments from the dataset of 448 investments. Excel generates a number between 1 and 448; that investment is copied from the dataset to the portfolio under construction. This is repeated as many times as needed to complete the portfolio given the portfolio size (e.g. 50 investments). Once the first portfolio is generated, average and median IRR and MIRR are calculated and recorded for that portfolio. The portfolio is then cleared, and a new portfolio is generated. This is repeated 1000 times to generate a returns "profile" for that specific size of portfolio. We specifically record the IRR and MIRR profiles as the percent of portfolios within specific categories (<0%, 0-10%, 10-20%, 20-35%, 35-50%, 50-75%, 75-100%, 100-250%, 250-500%, >500%).

We run this analysis for portfolio sizes from 5 to 450 investments in increments of 5 investments. This generates a total of 20,475,000 investments across 90,000 portfolios.

We sampled "with replacement." This means that each random investment selection chosen for the portfolio comes from the full dataset. A portfolio may therefore have multiple "copies" of the same investment. This sampling method ensures that portfolios are fully random reflections of the population distribution. Sampling "without replacement" means that once an investment has been selected into a portfolio it cannot be selected again for the same portfolio. This avoids duplicating investments within a portfolio, which might seem intuitively attractive. However, sampling without replacement requires the assumption that the data sample is not just representative of the population, but a perfect replica of the underlying probability distribution of possible investments. It requires that the selection of the same number of investments as the original dataset would be guaranteed to generate exactly the same returns outcome. Sampling with replacement only requires that the dataset is representative of the broader market, but allows for each marginal investment to be selected from the full population.

All prior studies rely on IRR to report returns, but we calculate both IRR and MIRR, based on the understanding that a given portfolio might represent the full set of angel investments available to

a given investor or group. MIRR accounts for variation in time horizons by requiring that cash returns be reinvested at an available reinvestment rate rather than the project IRR.

The full run parameters are as follows:

- Capital cost (for MIRR analysis) is set at 5%. This assumes that angels have an effectively infinite source of marginal capital at a relatively low cost. We assume that investors effectively set aside a pool of funds or can access funds via relatively low-cost borrowing methods (e.g. mortgage interest rate). In reality, because most of the investment outflows happen early in each portfolio, varying this parameter has little to no impact on the results.
- Reinvestment rate (for MIRR analysis) is set to 5%, 10%, 25%, 30%, and 35%. This facilitates exploration of outcomes when angels are required to reinvest cash inflows at rates below the previously reported returns of angel investing activity.
- Portfolio size varies from 5 investments to 450 investments in increments of 5 investments (e.g. 5, 10, 15, 20... 440, 445, 450 investments).

One additional note is required with regard to MIRR calculations. Because the investments vary in total hold time, portfolio returns necessarily reflect the hold time of the longest held investment in a generated portfolio. As discussed previously, we excluded the four investments that are held beyond 13 years.

## 5 Results

To explain the results, we first provide a specific example of a portfolio, then an example of a portfolio simulation, and then the full results of the analysis.

### *Sample portfolio*

Table 3 shows a sample portfolio generated by the analysis for a portfolio of 10 investments. We use an example with relatively few investments only because a table with many investments is difficult to provide in print. As explained previously, this portfolio was generated via the random selection of 10 investments from the full dataset. Certain characteristics of this portfolio should be noted. Every investment had some type of positive payout, even if that payout did not repay the full investment (total net cash <0).

Roughly 20% of the entire dataset had no positive payouts at all, resulting in the total loss of the investment. The IRR of this portfolio is 10.8%. For a reinvestment rate of 25%, the MIRR of this portfolio is 13.1%.



**Table 3: Sample 10 investment portfolio generated randomly from full dataset**

	Year					
Investment#	0	1	2	3	4	5
1	-25000		4000	3001		
2	-15000	613	1801			
3	-425000				1430000	
4	-100000					51000
5	-20000	80000				
6	-20000				40949	
7	-300000					316000
8	-250000	-100000	75000			
9	-300000					316000
10	-25000			56780		
<b>TOTAL</b>	-1480000	-19387	80801	59781	1470949	683000

***Portfolio simulation***

We now construct 999 more portfolios, each of which includes 10 investments, randomly selected from the dataset. Table 4 shows the *returns profile* of that simulation of 1000 portfolios of 10 investments each. The average and median IRR for 10 investments are 158.7% and 20.8% respectively. The average IRR for this portfolio is very high because there are portfolios with very high IRRs. The highest portfolio return was 2264.55%. It should be noted that 32 out of 1000 portfolios in this simulation do not have a reported IRR because the IRR calculation failed, either because the portfolio was all negative or all positive cash flows.

The *IRR returns profile* for the simulation shows 28.3% of portfolios generated IRR below 0%; 9.0% of portfolios generated IRR between 10% and 20%; 11.3% of portfolios generated IRR between 10% and 20%; 16.0% of portfolios generated IRR between 20% and 35%; 12.9% of portfolios generated IRR between 35% and 50%; 9.3% of portfolios generated IRR between 50% and 75%; 4.8% of portfolios generated IRR between 75% and 100%; 5.0% of portfolios generated IRR between 100% and 250%; .8% of portfolios generated IRR between 250% and 500%; and 2.56% of portfolios generated IRR >500%.

Analogous information for the *MIRR returns profile* shows that average and median MIRR for 10 investments are 121.55% and 22.3% respectively. Again, the average MIRR for this portfolio is very high because there are portfolios with very high MIRR. The highest portfolio return was 302.5%. It should be noted that 3 out of 1000 portfolios do not have a reported MIRR because the calculation failed, either because the portfolio was all negative or all positive cash flows. The IRR and MIRR returns profile for portfolios of 10 investments are compared visually in Figure 1.

### **Figure 1: MIRR and IRR returns profiles for portfolios with 10 investments**

The IRR analysis shows many more low returns portfolios ( $<0\%$ ) as well as many more high returns portfolios ( $>100\%$ ), as we would expect. For portfolios with longer hold time investments, MIRR will tend to converge to the reinvestment rate. This is an important observation that will be discussed in more detail.

#### **5.1 Full analysis results**

Now that we have explored the results for one portfolio size (10 investments) we can show the results of the full analysis simulating the same process across all portfolio sizes and for different reinvestment rates. First, we will show the result of varying portfolio size. Portfolio size varies from 5 investments to 450 investments. For this analysis, reinvestment rate is 15%, on the assumption that this represents a not-unreasonable returns goal for a high net worth individual investor with a large, diversified portfolio. The average and median IRR and MIRR across portfolio size are shown in Figure 2.

#### **Figure 2: Average & Median MIRR, IRR across portfolio size (reinvestment rate=15%)**

One of the more intriguing results of the simulation is the effect of portfolio size for very small portfolios ( $<20$  investments). Average IRR actually rises initially from the smallest portfolios and peaks around 75 portfolios. This emphasizes the significant variation in portfolios and the fact that only a few investments generate the vast majority of returns. Following the peak, average IRR drops through portfolio sizes until it levels out to the anticipated average of about 32%, the IRR of the full dataset. Average MIRR for small portfolios starts below the dataset average return, rising to a lower average which reflects the effect of the reinvestment rate (15%). Median IRR and MIRR start below the expected average and slowly converge to the average as portfolio size increases.

The portfolios returns profiles results are provided for IRR in Figure 3 and MIRR in Figure 4. Please note that these are simple extensions of the column charts shown in Figure 1, with data across all portfolios sizes (5 to 450 investments).

#### **Figure 3: IRR returns profile**

#### **Figure 4: MIRR returns profile for reinvestment rate = 15%**

As expected, IRR and MIRR measurements vary more widely for small portfolios than large portfolios, as shown in Figures 3 and 4. For small portfolio sizes, the results show many more portfolios with returns below 0% or greater than 100%.

We now consider the results of varying the reinvestment rate. We do not need to re-run the analysis for IRR; because IRR is calculated without an exogenous reinvestment rate (IRR assumes a reinvestment rate equal to the calculated IRR).

We reran the entire analysis with reinvestment rates of 5%, 15%, and 35%. Figure 5 shows the average MIRR across the varying reinvestment rates. Median MIRRs are not shown because they are not significantly different.

**Figure 5: Average MIRR across reinvestment rates 5% - 35%**

### *Effect of deal size*

Additional data visualizations are useful in presenting simulation findings. Figure 6 plots all of the investments to compare total investment amount and total return. We have overlaid the linear and 2<sup>nd</sup> order trend lines to show the best fit correlating investment and return.

**Figure 6: Return vs. investment for full dataset**

One problem with this analysis is that the largest cash investments and exit values span six orders of magnitude. To ensure that outliers were not obscuring a possible size-return relationship, we removed the six largest investments (most of which failed) and the five largest cash outs from the analysis. Doing so does not significantly change the results, shown visually in Figure 7. The linear trend and trend line fit are effectively unchanged. Evidence for an investment size – return relationship is very limited. Caution must be taken in applying causal relationships to these effects, but the first order conclusions appear relatively straightforward.

**Figure 7: Return vs. investment for dataset without outliers**

## **6 Discussion**

Discussion of findings are structured around three themes: deal-size vs. returns, portfolio-based angel investing, and practice and policy considerations.

### **6.1 Deal size**

A key debate in angel investing is the potential link between deal size and returns. As noted previously, angels and entrepreneurs often attribute venture failure to underfunding. A mantra of risk capital is “too little funding is worse than no funding at all.” This is based on the argument that underfunding a venture ensures failure because the organization will use the capital but fail to bring a viable product to market. Although angel investments usually incur smaller deal transaction costs than VC funding events (Mason and Harrison, 1996), diligence and transaction costs are relatively deal-independent. This again suggests that larger deals are more efficient. This economic reality has fueled significant increases in the average VC deal size (Sohl, 2003).

If a strong causal link existed between deal size and returns, we would expect to see some evidence of this in the AIPP dataset. The data suggests that size-return correlation for angel investments is modest, at best, or nonexistent. Figure 6 shows the raw correlation between investment capital and cash out. The correlation is positive but less than 1. More importantly, the linear trend is, statistically, a poor predictor of outcome ( $R^2 = .03$ ). A polynomial trend line marginally better fits

the data ( $R^2 = .08$ ), but only because of the outlier investments above \$2.5M that generated no returns. This result suggests that beyond a certain point, increasing angel investment size may actually generate lower returns. Removing the outliers, as previously noted, does not significantly change the results, as shown in Figure 7. The linear trend and trend line fit are effectively unchanged. Evidence for an investment size-return relationship is very limited. Caution must be taken in applying causal interpretations to these effects, in particular because the models cannot be thoroughly tested for significance. No other variables or factors were incorporated into the model. The analysis is only intended to suggest that the investment size-return relationship proposed in prior studies is not clearly supported by the AIPP dataset.

This is a potentially disheartening result for policymakers focused on co-investment mechanisms intended to increase deal size. Government-sponsored co-investment has been suggested as a viable mechanism to increase the impact of angel investing and facilitate more fast-growth entrepreneurial activity without significant diligence costs or the political issues associated with state-run venture funds (Baldock and Mason, 2015). The dataset does not appear to support such policies based purely on increasing deal size.

At the same time, our analysis cannot address hypothetical or counterfactual outcomes. It does not show whether increasing the size of a *specific* deal would generate higher returns or not. The analysis assumes a relatively efficient market for angel investment deals: on average good deals are funded and, *pari passu*, bad deals are not. In entrepreneurial ecosystems with below-market levels of available angel capital, co-sponsoring deals might be an effective mechanism to raise the rate of angel-funded entrepreneurial activity. Because angel investing tends to be more local and regional than organized VC, state-sponsored co-investing might effectively target areas with below-market levels of angel capital to encourage high-growth venture activity. Clearly, further research on this particular relationship is required.

## 6.2 Portfolio returns to angel investing

As expected, portfolios with roughly the same number of investments as the full dataset show the same average returns when calculated with IRR (32%). Of much more interest are the profile of large portfolios, the expected returns to smaller portfolios, and the implications of using MIRR rather than IRR as the metric. We discuss each in turn.

### ***Risk-return profile of large portfolios***

The simulation facilitates a much more sophisticated approach to understanding expected returns than a simple IRR calculation of the entire dataset. Figure 2 shows that while the average IRR of very large portfolios is as expected, the median IRR is rising to roughly the same level from much lower numbers. At 450 investments, the median IRR is below 30%. In other words, even at this very large portfolio size, outlier portfolios with high returns are skewing the average return higher. We can see this visually in Figure 3. The majority of portfolios generated (N=450 at the far right side of the graph) fall into the 20%<IRR<35% range. Approximately 30% of the portfolios generate IRRs greater than 35%, including approximately 5% of portfolios generating returns greater than 75%. No portfolios generate negative returns, and about 20% of portfolios generate IRRs between 0-20%.

We suggest that these are key findings. Assuming that the dataset is a reasonable representation of the underlying population of angel investments, the analysis suggests that it may be effectively impossible to reduce the risk of generating poor risk-adjusted returns, even without addressing the reinvestment rate issue. Most practitioners and scholars have argued that angel investing is inherently riskier than VC investing due to multiple factors, including less professional deal vetting and diligence, less effective deal negotiation, and more uncertainty associated with technology and market (e.g. Mason and Harrison, 2004). Angel investors and policymakers should be aware that while the risks of poor returns ( $<20\%$ ) can be mitigated by increasing portfolio size, they cannot be eliminated altogether.

### ***Returns profile of smaller portfolios***

Findings reveal that the risks and returns increase as portfolio size decreases, as expected. The effect of average IRR becomes evident when portfolio size falls below 200 investments. It is important to note, however, that while the average IRR at 200 investments is roughly the same as for 450 investment, the returns profile is actually quite different. At 200 investments, approximately 1/3 of portfolios generate  $20\% < \text{IRR} < 35\%$ . While the total number of outperforming portfolios has remained relatively constant, the number of significantly outperforming portfolios ( $\text{IRR} > 75\%$ ) and the number of underperforming portfolios ( $\text{IRR} < 20\%$ ) both increase. The median IRR has fallen to about 28%.

Between 200 and 100 investments per portfolio, the average IRR rises to approximately 40%, while median IRR continues to fall to roughly 25%. The returns profile is even more revealing. Nearly 40% of all portfolios generate returns below 20%, and more than 10% of all portfolios generate returns below 10%. At 50 investments per portfolios, the average IRR approaches 45%. Now nearly 20% of all portfolios are generating returns below 10%. This escalates rapidly as portfolio size approaches the level recommended by prior research. At 20-25 investments, average IRR actually may exceed 50%, but 30% of all portfolios are generating returns below 10%. In fact, roughly 20% of all portfolios are generating negative IRR.

Below 20 investments it should be clear that there is significant variability in results; 30% of all portfolios generate negative IRR; 40% of portfolios generate IRR between 0% and 35%; and 30% of portfolios generate returns above 35%. Roughly 20% of portfolios generate returns above 75% and nearly 10% generate returns above 100%.

This key finding suggests that generating reasonable risk mitigation (reducing probability of negative or poor risk-adjusted returns) appears to require significantly more than the 12-20 investments suggested by prior research. A minimum of 50 investments is required to bring the risk of  $\text{IRR} < 10\%$  below 1 in 5 portfolios. Portfolios size of 150 investment brings that risk below 1 in 10 portfolios. The danger of small group or individual investing emerges when a very few success stories overshadow widespread failure. For example, assume that 100 angels each invest in 5 ventures. Only one or two (if any) angels would be likely to generate strong returns, while the vast majority would experience flat returns or total losses. Media and network-based attention on the successes would likely hide large cohorts of unsuccessful, discouraged individual angels unlikely to continue to make investments.

The simulation results suggest that *consistently* high angel returns requires a large, long-term effort. A few assumptions help clarify the underlying challenge to portfolio-based angel investing. Assuming that the average deal size is \$500,000, an angel group would need to invest \$50 million to have 90% certainty of achieving greater than 10% returns. If the group has 20 members, each must invest \$2.5 million. While some leading angel groups, such as Band of Angels in the U.S., may have the wherewithal to participate at this level, anecdotal evidence suggests that the vast majority of groups and angels are not this active. For example, the Central Texas Angel Network (CTAM) has invested \$62 million from 140 angels across 110 companies. Since CTAM describes itself as one of the five most active networks in the U.S., it is probably safe to assume that the majority of angel networks in the U.S., and by extension the rest of the world, are not operating at large enough scale to ensure above average portfolio returns.

### ***Use of MIRR rather than IRR for angel portfolio returns***

The use of MIRR rather than IRR solves at least one returns measurement issue but generates additional problems. The significant advantage of MIRR lies in the ability to set a reinvestment rate rather than assume that positive cash flows may be reinvested at the same rate as the underlying investment. From a practical perspective, this simply means that as angels receive cash returns from investments they are always able to immediately re-invest those in opportunities with the same IRR expectations.

This would seem to be, at face value, a flawed assumption. Our anecdotal observations of angel networks in the U.S., Canada, and UK suggest that angels do not generally have or exercise the option to immediately reinvest cash returns. Rather, individual investments are seen primarily as one-off investments, and positive cash flows from those investments are returned to the investors' broader investment portfolio. The assumption is also problematic from a purely methodological standpoint. The simulation analysis requires that the portfolio automatically represents all of the angel investments being made by the individual or group.

We explored the implications of using MIRR instead of IRR in the simulation. We used a "base" reinvestment rate of 15%, well below the average IRR of the entire dataset, but a not unreasonable upper level goal for an individual's total investment portfolio. The results are striking, if not surprising. Average MIRR is significantly and consistently lower than average IRR, rising from approximately 13% at 5 investments to a stable rate of 20% by around 50 investments. The returns profile (Figure 4) shows how this stability forms across returns ranges. Once portfolio size reaches 50 investments, less than 30% of portfolios generate returns below 20% and less than 15% of portfolios generate returns greater than 35%.

Why does MIRR generate such different returns? We suggest the answer is in the investment hold time. Although some of the investments in the dataset exit quickly (within 5 years), many investments achieve exits after 5 years or after 10 years. Because we are evaluating the MIRR of the entire portfolio, the reinvestment rate comes into play for all investment returns through the year of the final exit event. The longer the hold time of the portfolio, the greater the effect of the reinvestment rate.

As shown in Figure 5, MIRR is driven significantly by the reinvestment rate, especially as portfolio size increases. This is an important observation, even if it follows in a more straightforward way from the mathematics. Understanding angel investing from a portfolio perspective requires careful considering of the reinvestment opportunities and alternative reinvestment rates. Imagine, for example, that an investor makes two investments of roughly equal size. One pays out well within 2 years, but the other is held for more than 10 years. If the cash payment from the first investment is not reinvested in new angel deals, then the measurement of returns of the overall portfolio will likely be dominated by whatever rate of return the investor receives on the reinvestment of the funds generated by the first investment.

### **6.3 Practice and Policy Considerations**

Our study generates three important recommendations for angels and angel groups. First, angels should fully appreciate the risk-reward profile of angel investing, including the benefits and limitations of portfolio-based investing. Simulation results clearly suggest that risk mitigation strategies are likely out of reach of most angel investors, including most “super-angels.” The portfolios size needed to achieve significant risk mitigation (>50 deals) is also greater than most angel groups attain. In comparing angel and VC risk-reward profiles and returns performance, we need to recognize differences that include VC fiduciary responsibilities to maximize returns (i.e. by GPs on behalf of their LPs), use of non-financial criteria in making investment decisions by angels, investment holding time differences, availability and deployment of value-added services, etc. (Cumming and Johan, 2010).

Second, angels should be cognizant of the impact of reinvestment rate on returns calculations. Recent research suggests that angels are “patient investors” by default rather than plan. While this likely benefits individual ventures and entrepreneurs, the long hold time of angel investments may significantly reduce effective portfolio returns if positive cash flows are not being reinvested in a comparable asset class. Angel groups might consider fund pooling mechanisms and a rolling basis for investments to ensure that angels seeking to obtain the highest portfolio-based returns have the ability to make such reinvestments.

Many angel investors and investing groups face the challenge of an escalation of commitment - the tendency to invest additional resources in an apparently losing proposition, influenced by effort, money, and time already invested (e.g. Staw 1981; Brockner 1992). Many ventures that receive angel funding will seek additional funding either as part of their planned growth strategy or as an unplanned reaction to unforeseen circumstances. As in the case of institutional venture capital (Birmingham et al 2003; Devigne et al 2016), angels that are already invested must carefully consider whether to reinvest. Reinvesting in such circumstances may therefore be subject to different criteria as compared to the initial investment decision and may protect their ownership share but increases total exposure.

Finally, angels should employ a clear strategy with regard to deal size and total investment planning. We found no direct evidence of benefit from larger investments. While companies may fail without capital infusions, re-investment increases the hold time for deals that may already be in trouble, with the potential to significantly decrease portfolio returns. While further research is

clearly required, angels and angel groups would likely benefit from more explicit planning and expectations to maximize the impact of investment amounts and minimize the risk of poor long-term return.

Our study also generates three recommendations for policies which attempt to encourage and support angel investing. First, policymaking should focus on private, group-based investing rather than government-organized or widely distributed/isolated angel activity. Minimum scale for ensuring appropriate risk-adjusted returns exceeds the capacity of all but the wealthiest and long-term focused investors.

Second, government entities should be as focused on angel network *longevity* as investment activity. Angel networks that make less than 50 investments have roughly a 45% probability of generating IRR less than 20%, and roughly 20% probability of generating IRR below 10%, not accounting for reinvestment rate. Such networks may tend to be transient as disillusioned investors drop out or reduce their investment activity. Government entities might most effectively support network longevity through subsidized training, diligence costs, or even administrative support. Rather than co-invest in deals to increase deal size, public money may be better spent co-sponsoring network administration to sustain networks and maximize investment learning. As mentioned earlier, a deal size-returns relationship suggested in prior studies is not clearly supported in our simulation results.

Third, we acknowledge that tax incentives and co-investing represent potentially viable tools to encourage angel investing activity. Tax incentives help shield angels from losses associated with failed investments. Co-investing may give angels and angel groups more leverage in negotiating deals and ensuring that high-growth ventures raise enough money to reach key milestones. However, we caution that both have significant drawbacks. Co-investing may encourage larger investments that tie up disproportionate amounts of capital and tax incentives may attract less serious or capable investors seeking tax relief.

Our study suggests that such tools could be used discriminately depending on the pool of available angel deals. Public entities might directly subsidize angel investing (tax incentives) while the population of opportunities is relatively low, because angels cannot easily reinvest positive funds in more deals. Tax incentives would offset the necessarily low return rate resulting from the requirement to reinvest proceeds in alternative asset classes with lower expected returns (e.g. mutual funds). Once the start-up population is large enough to enable the re-investment cycle, public entities could shift to co-investment to increase the number of investments. With a larger pool of deals available, co-investment could help angels and angel groups quickly reinvest positive returns.

## **7 Conclusions**

This paper addressed the question of whether angel investing generates attractive returns. Given the high levels of variability reported for individual angel investment returns, we hypothesized that



much larger portfolio size ( $N > 25$ ) is required to provide significant protection against returns variability and low IRR portfolio outcomes. Our study offers a number of contributions.

First, we extend prior studies that examine angel returns by exploring the link between portfolio size and investment returns. Monte carlo simulation of data from the largest angel returns study to date (AIPP) further emphasizes the high risks associated with angel investing and empirically validates investment challenges faced by individual angels and small angel networks in attempting to generate attractive returns. Our study provides further evidence that large successes and exits are not representative of typical angel investments.

Second, in contrast with prior studies, we show that portfolios with more than 50 investments are required to significantly minimize risk of poor returns. We show that similar scale is required to maximize returns potential, as smaller portfolios also have a lower average IRR. This has important implications for angel investing practice, where achieving attractive returns favors angels in larger, established angel groups over individual angels, or angels in smaller groups.

Third, we show that reinvestment rate is a critical element in measuring angel returns. If angels can reinvest cash returns in more, comparable investments, then portfolio returns may actually be slightly higher than previously reported. If angels cannot constantly reinvest cash returns in more investments, then real portfolio returns are significantly lower than previously reported.

Fourth, we show that public policies to stimulate larger angel investments may be misguided, as our findings do not support arguments linking deal size to returns. We encourage policymakers, who reasonably view angel investing as an important component of economic development policy, to focus more on angel network syndication and network longevity, rather than deal size and tax incentives for loss-reduction.

## **7.1 Limitations and future research**

We suggest that simulation analysis represents a powerful tool for exploring portfolio-based returns to angel investing. At the same time, it incurs specific limitations that should be carefully considered. The simulation is restricted to the investment sample of the database and the accuracy of the simulation results are limited by how effectively the sample replicates the real population of angel investments. The authors suspect that this dataset, along with most other angel datasets in the literature, over-represents relatively high-profile, sophisticated angel investors and is further characterized by systematic upward bias in reported returns.

This supports the view of DeGenarro and Dwyer (2014), who suggest the angel groups who participated in the AIPP study are not a random sample of all angel investors. They identify the high percentage of investments in the study that resulted in an IPO, but found that many angels in the AIPP data invested in the same IPO, with 13 of the 56 IPO investments being the same deal. We postulate that the returns reported in most angel investment research are over-estimates of the full population of angel investing activity. We suggest that large scale estimation of the real population of angels' deals is urgently required to confirm whether extant dataset samples are representative or not. We strongly encourage researchers with proprietary datasets to consider

pooling such datasets, both to examine subpopulation differences as well as to enable more powerful and sophisticated simulation procedures.

Aside from the research opportunities already developed, we suggest five themes for further study. First, MIRR-based results are directly affected by total portfolio hold time. While this is a fundamental limitation of the calculation, it could be possible to explore the implications of setting (arbitrary) hold times for investment planning purposes. We would expect that overly short hold times would reduce returns, there might be an optimal time frame for portfolio planning, given that long hold times reduces MIRR to the reinvestment rate. In other words, we expect that the relationship of MIRR to hold time would be an inverted “U” shape, and that it may be possible to estimate an optimal hold period for angel investments from a portfolio-based perspective.

Second, this study and all of the prior angel returns studies have calculated IRR/MIRR for portfolios in which all investments occur in Year 0. While this is an extremely convenient approach, it is *prima facie* wrong. Neither angels nor angel groups make all investments in one year. Investments tend to be spread out over extended lengths of time. Again, it is unclear what the implications are for overall portfolio returns, but it should be investigated.

Third, the analysis presented does not take into account tax implications. Positive cash returns should generally be expected to be taxed at a prevailing capital gains rate (15% for long-term gains in the U.S.); investment losses generate a tax benefit. This process would decrease the value of short term gains and increase the value of short and medium-term losses. The implications for total portfolio returns are difficult to predict, but should be investigated.

Fourth, a key question for angel portfolio investing is the extent to which escalation of commitment occurs as a self-justificatory strategy (Brockner 1992), and if so, whether this escalating commitment has positive or negative implications for overall portfolio investment returns. We were not able to address this question directly in our current treatment, but anticipate addressing it in a follow-up study.

Finally, the AIPP dataset does not provide information to measure possible learning effects, so the simulation effectively treats all investments as equally likely. DeGenarro and Dwyer (2014) specifically suggest that syndicate-based learning results in significantly higher investment returns. The form of learning may be explicit or tacit knowledge, or even encoded within the syndicate’s network of internal or external relationships. Regardless, such learning effects are only accessible if the network retains enough investors to make investments and maintain infrastructure to store and extract learning as needed by investors. This suggests that smaller angel networks may benefit from actively seeking to share diligence and syndication of deals with other angel networks. The relationship between learning effects and returns across different angel groups is a potentially promising area for further study.

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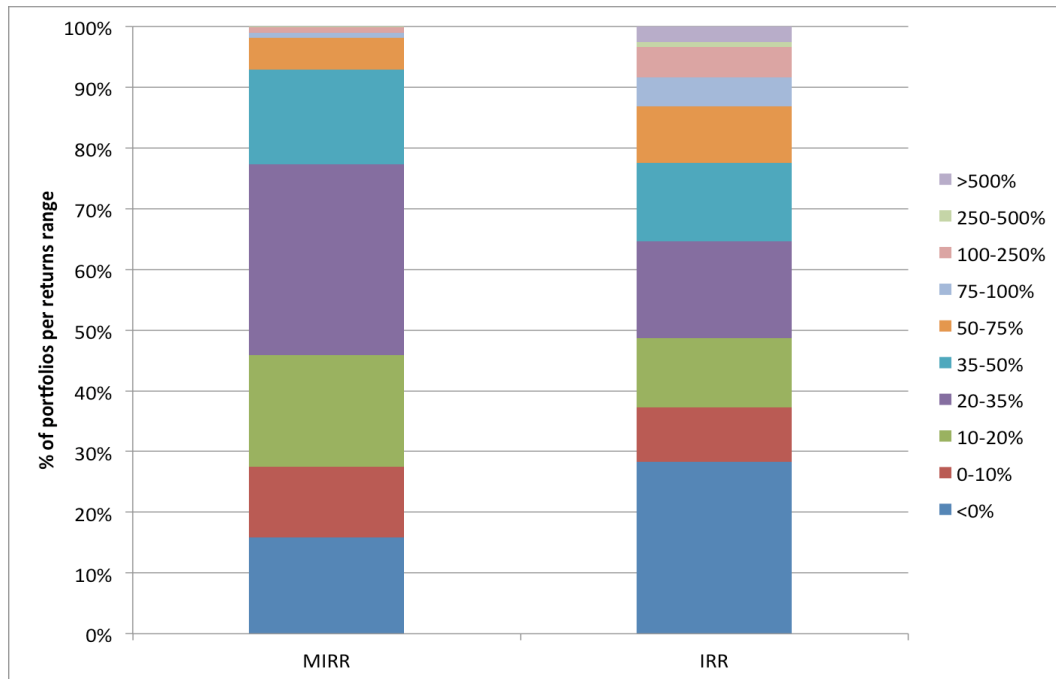
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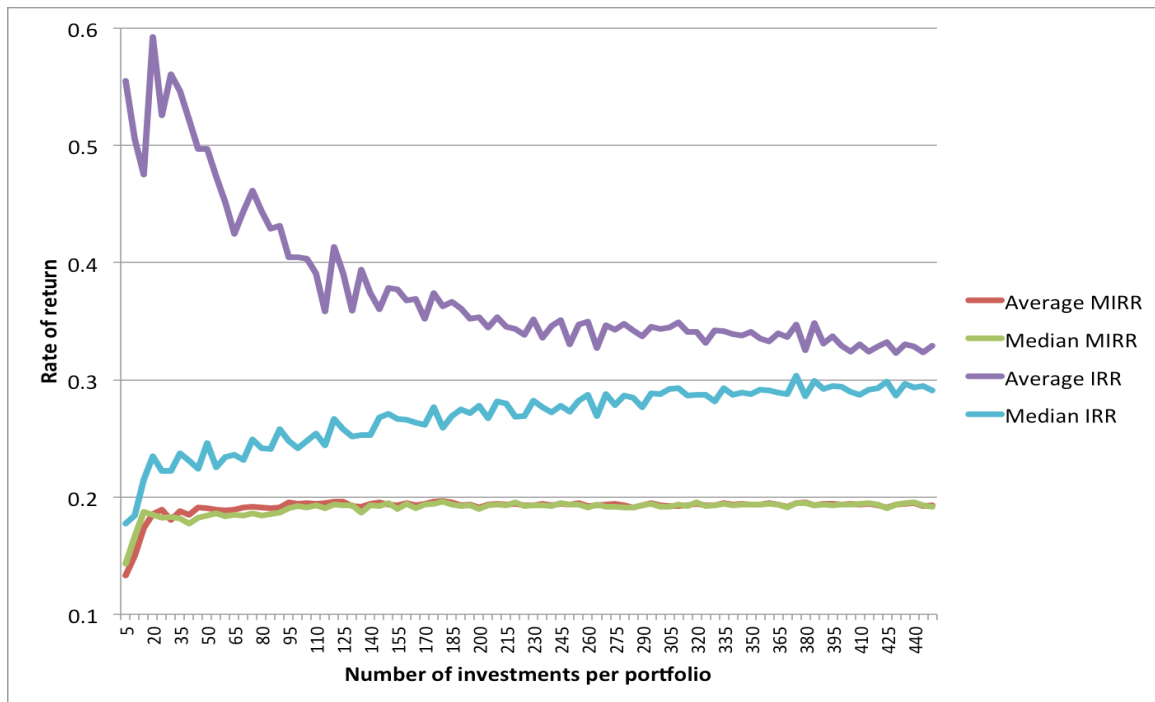
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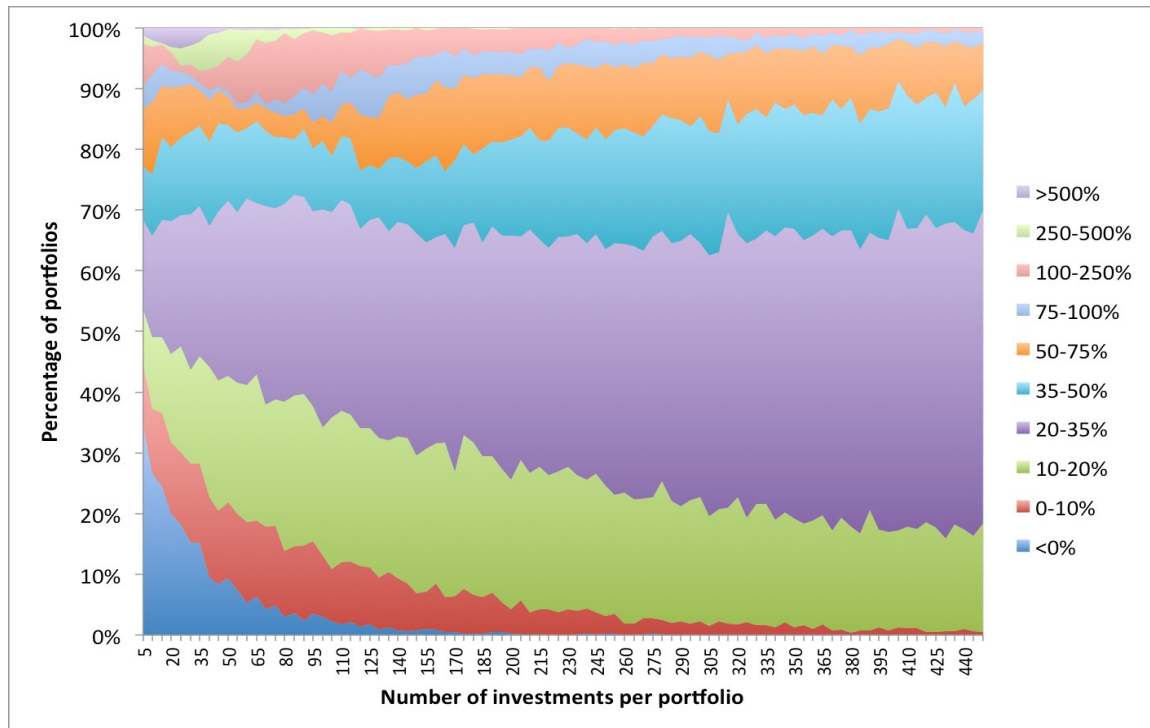
**Figure 1: MIRR and IRR returns profiles for portfolios with 10 investments**



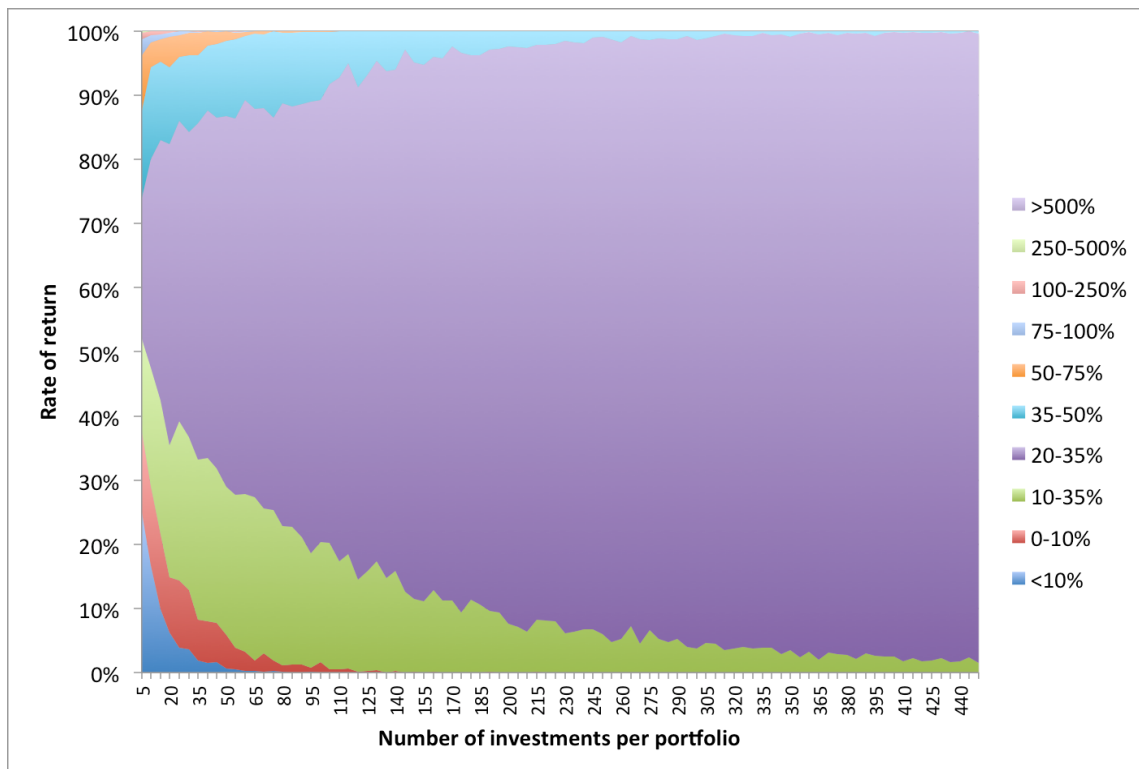
**Figure 2: Average & Median MIRR, IRR across portfolio size (reinvestment rate=15%)**



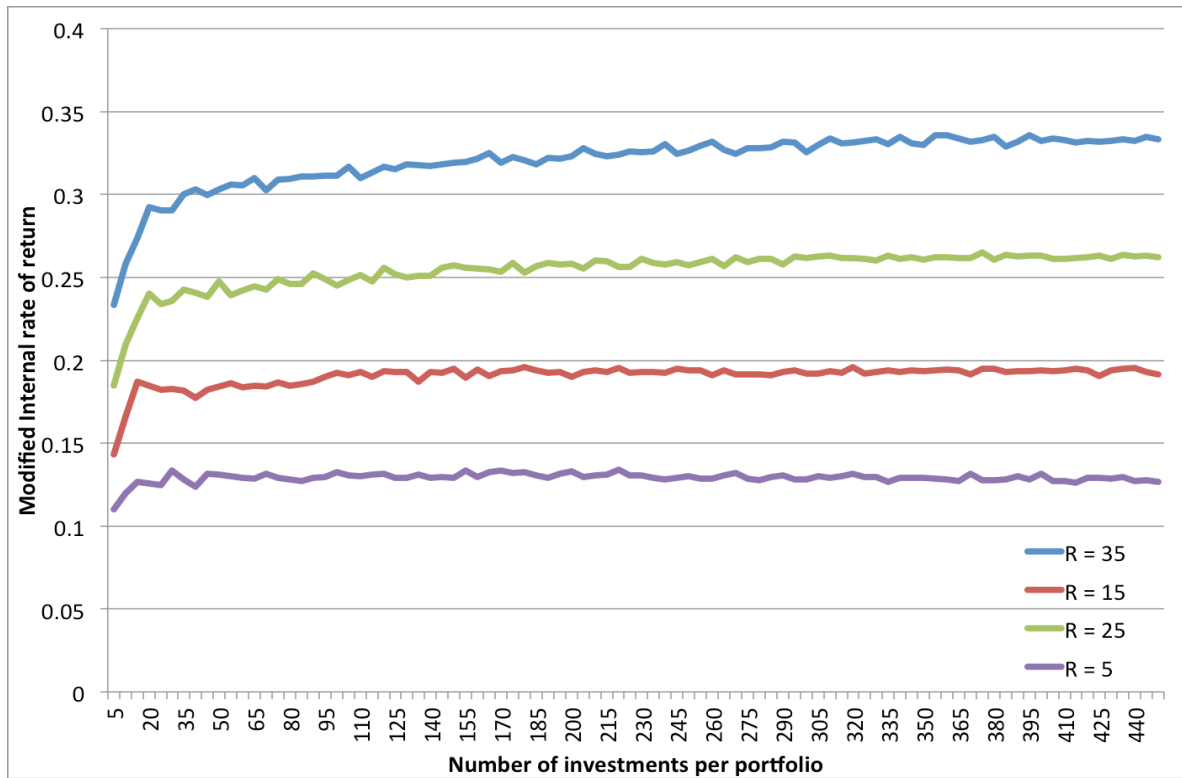
**Figure 3: IRR returns profile**



**Figure 4: MIRR returns profile for reinvestment rate = 15%**



**Figure 5: Average MIRR across reinvestment rates 5% - 35%**



**Figure 6: Return vs. investment for full dataset**

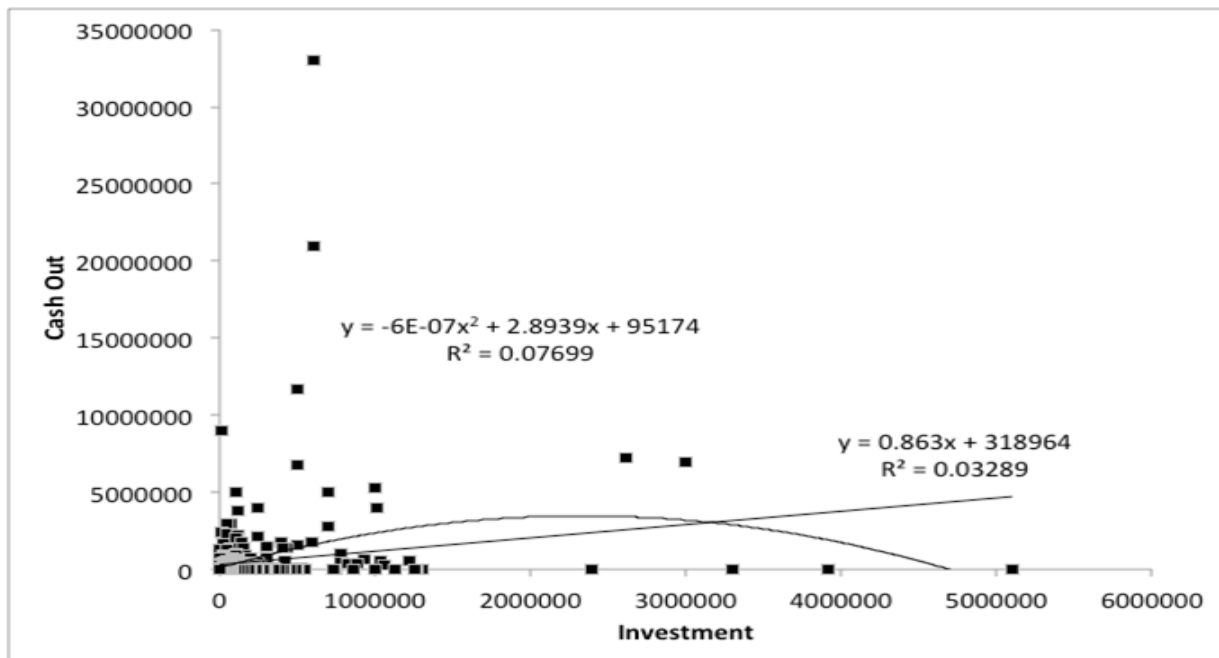


Figure 7: Return vs. investment for dataset without outliers

